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Title: EREBUS Coupled Hydrodynamic Radiographic Dynamic Reconstruction & Limited View Reconstructions

Author(s): Klasky, Marc Louis; Bouman, Charles; Disterhaupt, Jennifer Lynn Schei; Espy, Michelle A.; Fessler, Jeffrey; Hossein, Maliha; Guardincerri, Elena; Hovey, Luke Douglas; Korobkin, Oleg; Lahiri, Anish; McCann, Michael; Nadiga, Balasubramanya T.; Patterson, Brian M.; Pfister, Luke Anthony; Sjue, Sky K.; Ravishankar, Sai; Sanzo, Dean Lawrence; Wilcox, Trevor; Wohlberg, Brendt Egon

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EREBUS Coupled Hydrodynamic Radiographic Dynamic Reconstruction & Limited View Reconstructions

Marc Klasky, P-3
Charles Bouman, Purdue
Jennie Schei Disterhaupt, P-1
Michelle Espy, E-6
Jeff Fessler, University of Michigan
Elena Guardincerri, P-3
Maliha Hossein, Purdue GRA
Luke Hovey P-3, Post-DOC
Oleg Korobkin, CCS-7
Anish Lahiri, University of Michigan
Michael McCann, MSU Post Doc
Balu Nadiga, CCS-2
Brian Patterson, MST-7
Luke Pfister, P-1
Sky Sjue, P-1
Sai Ravishankar, MSU
Dean Sanzo, P-3
Trevor Wilcox, XTD
Brendt Wohlberg, T-5

Los Alamos NATIONAL LABORATORY EST. 1943

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NNSA National Nuclear Security Administration
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Computational Imaging at LANL

https://int.lanl.gov/org/ddste/aldps/mst/mst8/imaging/index.shtml

Initiative for Scientific Imaging (ISI)

Locations at LANL where imaging is practiced.

Contact

Cristina Garcia-Cardona

Marc Klasky

Youzuo Lin

Sven Vogel

Brendt Wohlberg

The *Initiative for Scientific Imaging* (ISI) is a focal point for the interdisciplinary community of LANL scientists working on imaging problems. Our goals are to facilitate greater communication among these scientists, as well as between experts in specific imaging problems and mathematicians and engineers with relevant expertise, and to serve as an umbrella organization to seek funding in this area.

Imaging at LANL

- Radiography & Tomography
- Coherent Imaging
- Seismic Imaging

ISI Seminars

- 2021-03-25 13:00 (Anders Kaestner/PSI)
- 2021-03-11 11:00 (Doğa Gürsoy)
- 2021-02-25 11:00 (Soumendu Majee)
- 2021-02-11 11:00 (Singanallur Venkatakrishnan)
- 2021-01-28 11:00 (Laura Smilowitz)
- 2020-12-17 11:00 (Sanna Sevanto)
- 2020-11-05 11:00 (Kevin Lamb)

ISI Members

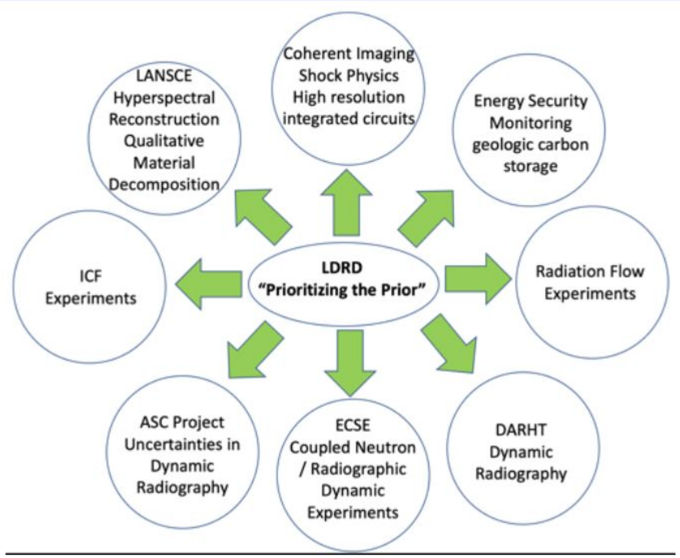
- Thilo Balke (computational imaging)
- Cristina Garcia-Cardona (computational imaging)
- Luke Pfister (computational imaging)
- Brendt Wohlberg (computational imaging)
- John Barber (coherent imaging)

Resources

- Mailing Lists
- Software & Tutorials
- Imaging Groups & Facilities
- Conferences

SCICO: Scientific Computational Imaging Code

- Open-source software for computational imaging
  - Developed by Luke Pfister (P1), Brendt Wohlberg (T5), and Cristina Garcia-Cardona (CCS3)
- Powered by Python & JAX
  - Transparent execution on CPU, GPU, and multiple GPUs
  - Just-in-time compilation and powerful automatic differentiation
- Supports standard regularization (Tikhonov) and state of the art (Plug-and-Play Deep Denoising Priors)
- Model based reconstruction + deep learning in a single package!



Current Projects

- ASC Development of Coupled Radiographic & Hydrodynamic Code to assess uncertainties
- Extremely limited view tomographic reconstruction algorithm Development LDRD
- Application of de-Scattering & poly-energetic energy tomography for determination to HE inspection Pathfinder
- DTRA Emergency response
- Application of coupled radiographic & hydrodynamic code to rad Flow experiments
- Hydro-Program HART Tool Box development
- Global Security Project
- NA-22 Development of multi-modality& 3D Machine Learning Algorithms

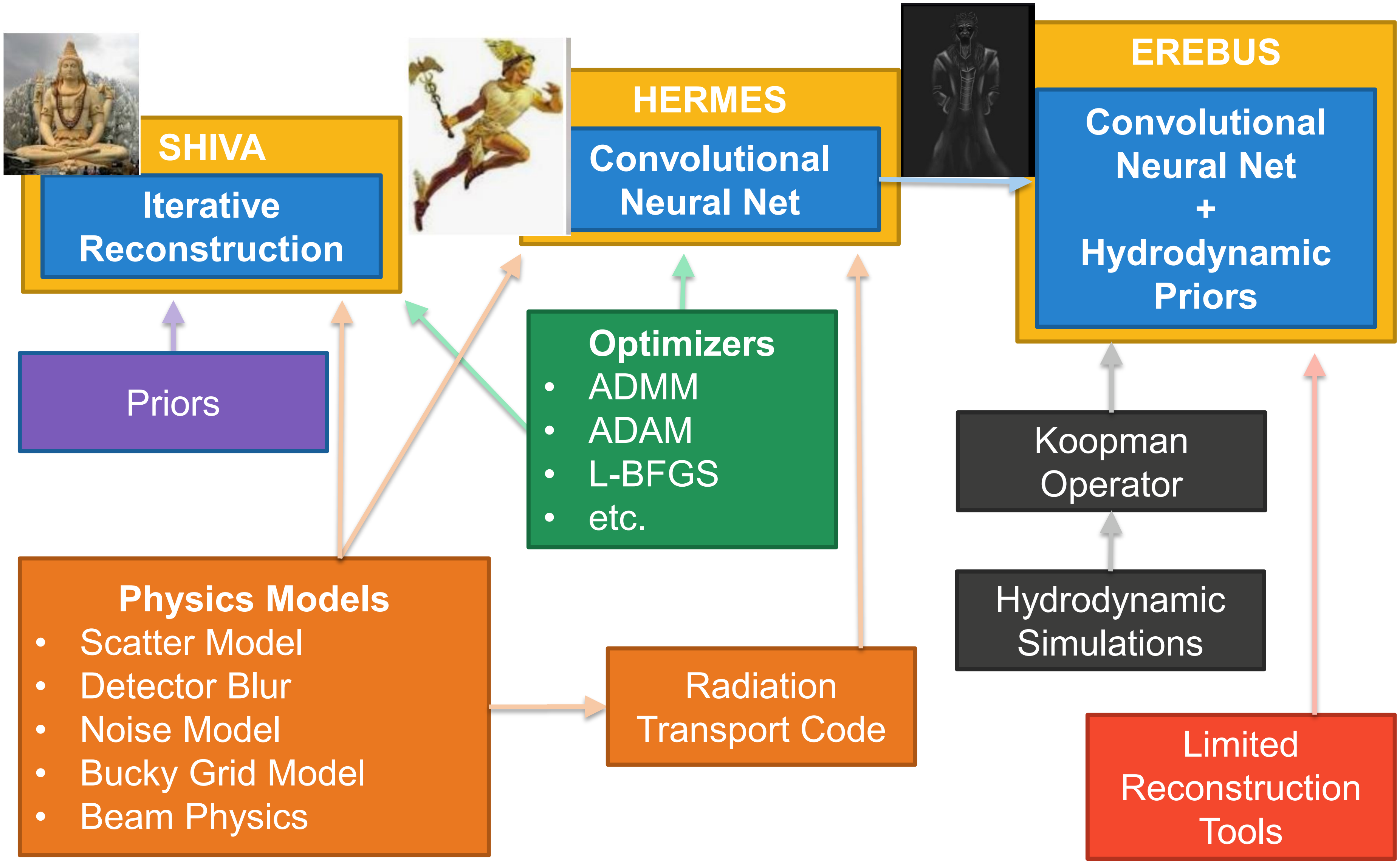
Objectives

1. Reconstruct a series of highly accurate density fields of a three-dimensional object from a time series of radiographic projections to inform hydrodynamic parameter estimation and/or model selection.
2. Develop a quantitative method for assessing density uncertainty and subsequent analyses.
3. Develop methods to address three-dimensionality.
4. Develop a technique to advance the density field in time to allow for subsequent calculations.

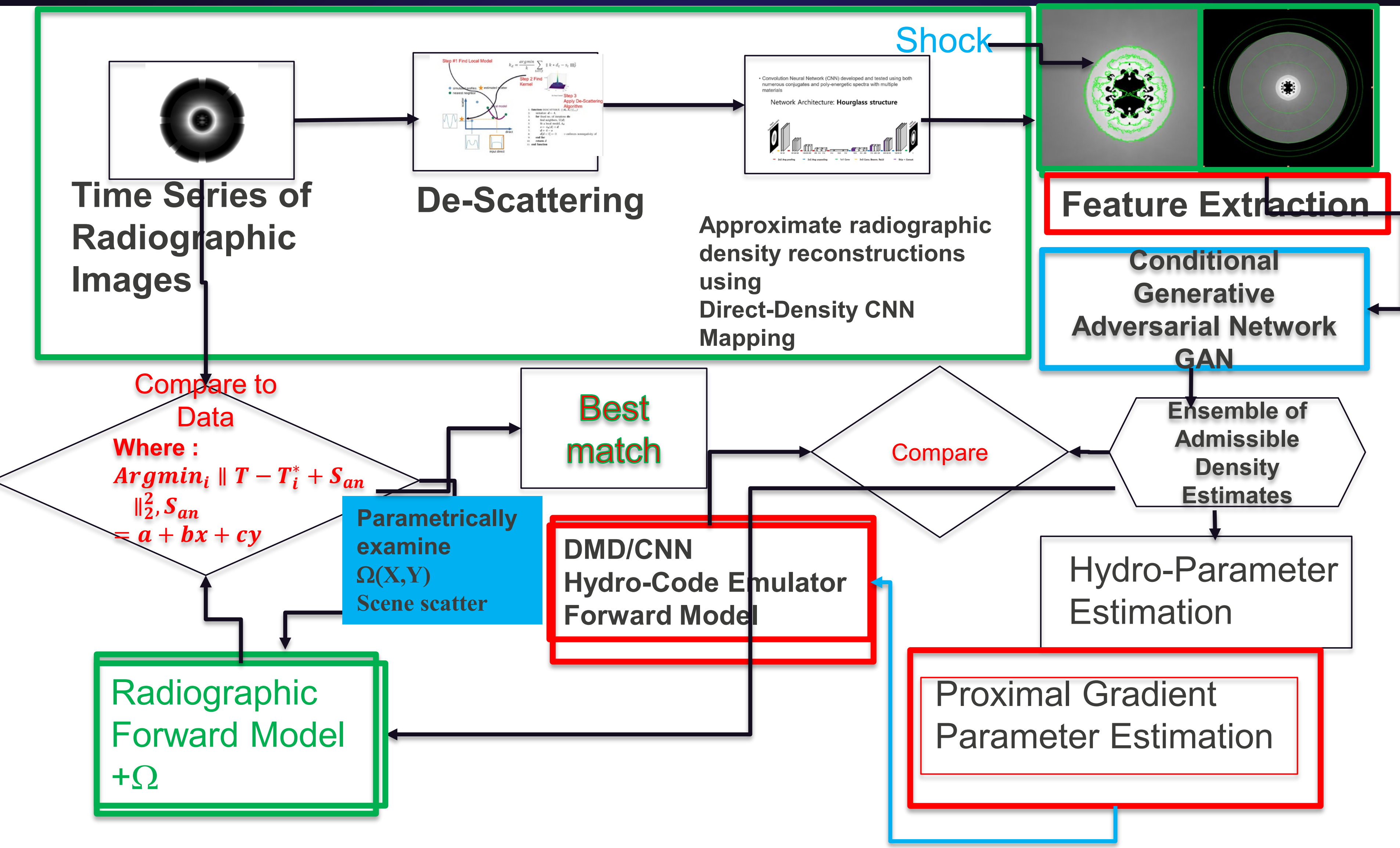
Simulations

- In this presentation a series of hydrodynamic simulations have been performed to generate an ensemble of two-dimensional Richtmyer Meshkoff instability simulations.
- The simulations utilize a Tantalum shell with an initial inward velocity and a perturbation on the inner shell surface of the form:
  - $R = Ro + \delta + Sin(k\ \theta)$
  - Where:
    - » Ro is the unperturbed inner radius
    - » Δ is the amplitude of the initial perturbation on the inner surface
    - » K is the wave number of the perturbation

Hydrodynamic and Reconstruction Toolbox (HART)



EREBUS: Coupled Hydrodynamic/Radiographic Reconstruction Algorithm for Physics Informed Density Reconstructions

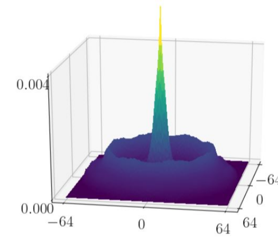


Scatter Approach

Step #1 Find Local Model

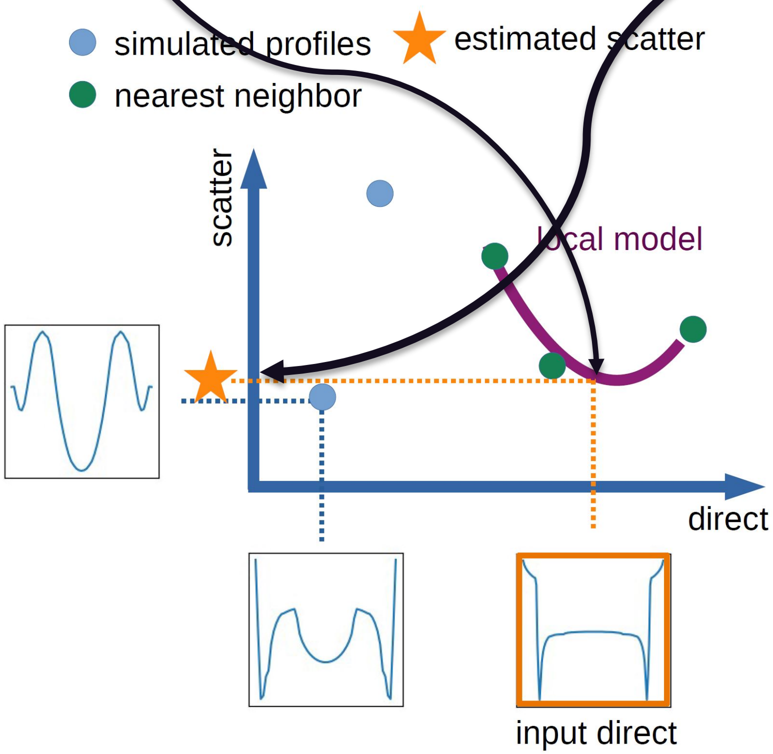
$$k_d = \frac{argmin}{k} \sum_{t \varepsilon U(t)} \| k * d_t - s_t \| \|_F^2 \;\; s.t. k \geq 0$$

Step 2 Find Kernel



(b) local kernel

Step 3 Apply De-Scattering Algorithm



function DESCATTER($\boldsymbol{t}$; $\{(\boldsymbol{d}_t, \boldsymbol{s}_t)\}_{t=1}^{I}$)
  initialize: $\boldsymbol{d} \leftarrow \boldsymbol{t}$,
  for fixed no. of iterations **do**
    find neighbors, $\mathbb{U}(\boldsymbol{d})$
    fit a local model, $\hat{\boldsymbol{s}}_{\boldsymbol{d}}$
    $\boldsymbol{s} \leftarrow \hat{\boldsymbol{s}}_{\boldsymbol{d}}(\boldsymbol{d}) + \boldsymbol{d}$
    $\boldsymbol{d} \leftarrow \boldsymbol{t} - \boldsymbol{s}$
    $\boldsymbol{d}[\boldsymbol{d} < 0] \leftarrow 0$ ▷ enforces nonnegativity of
  end for
  return $\boldsymbol{d}$
end function

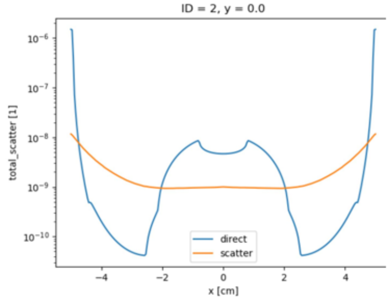
Treatment of the Scattered Radiation via the Local Kernel Model

Scatter and Direct components of Transmission

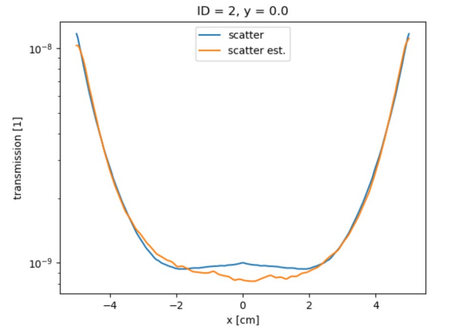
Scatter/Direct Signal

Estimated Scatter/ True Scatter

High Scatter Case

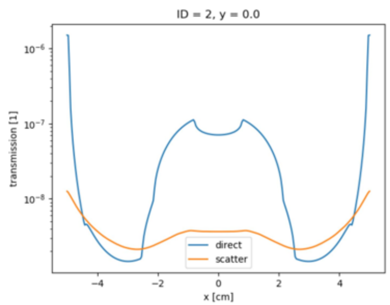


Object 1

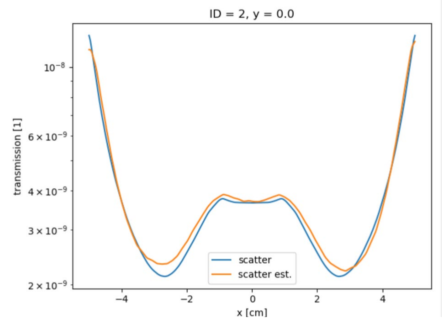


In general we have achieved excellent de-scattering results.

Medium Scatter Case

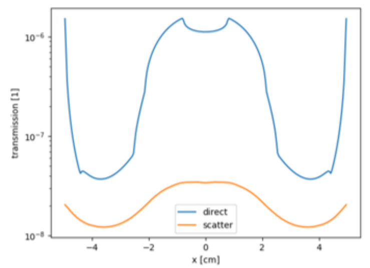


Object 2

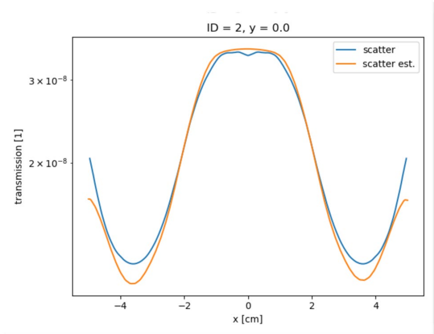


Impact on density reconstructions will be addressed later in the presentation.

Low Scatter Case



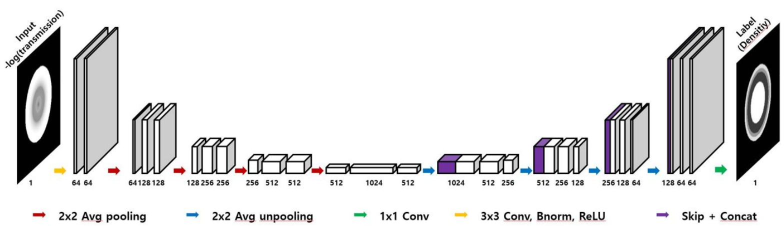
Object 3



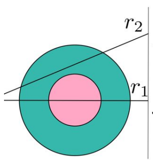
Inversion techniques for density inversion using neural network for radiographic inversion RADNET & Onion Peeling

- Convolution Neural Network (CNN) developed and tested using both numerous conjugates and poly-energetic spectra with multiple materials

Network Architecture: **Hourglass structure**

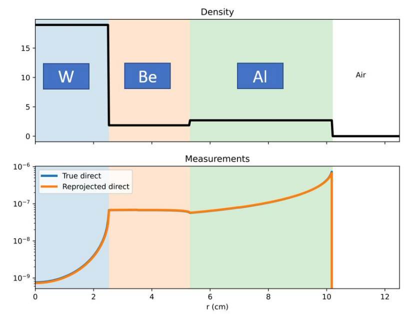


- Start with library of material densities and cross sections, $\{\xi_i(E), \rho_i\}$
- Detect material interfaces from radiographic transmission
- Project a ray through the outermost layer; determine outermost material
- Fix outermost material and repeat for next layer

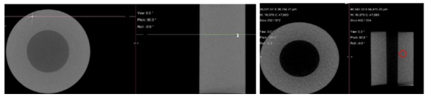


$$\int I(E) e^{-l_2(r_2)\rho_2\xi_2(E)} dE$$

$$\int I(E) e^{-l_1(r_1)\rho_1\xi_1(E) - l_2(r_2)\rho_2\xi_2(E)} dE$$



Note: We are currently utilizing our combined CNN/de-scattering algorithm for a multitude of scientific of scientific inquires.



PBX Density Experiment

Pathfinder

Gold Horn

CNN results for direct-to-density mapping generally show excellent reconstruction.

Reconstructions are almost instantaneous

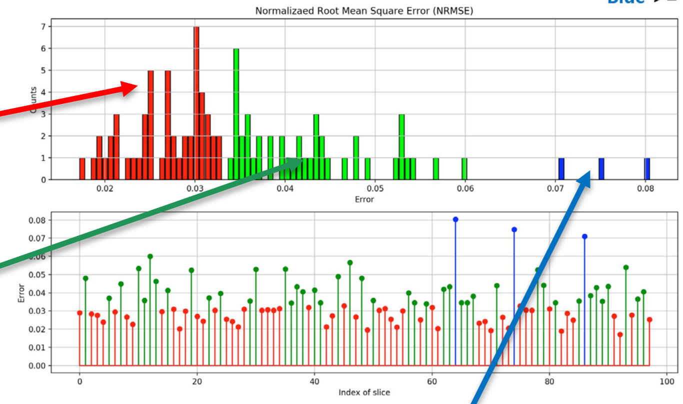
- Histogram shows frequency of percent density RMS errors for test cases

Red < 2.5 %

2.5 % <= Green < 7.5 %

Blue >= 7.5 %

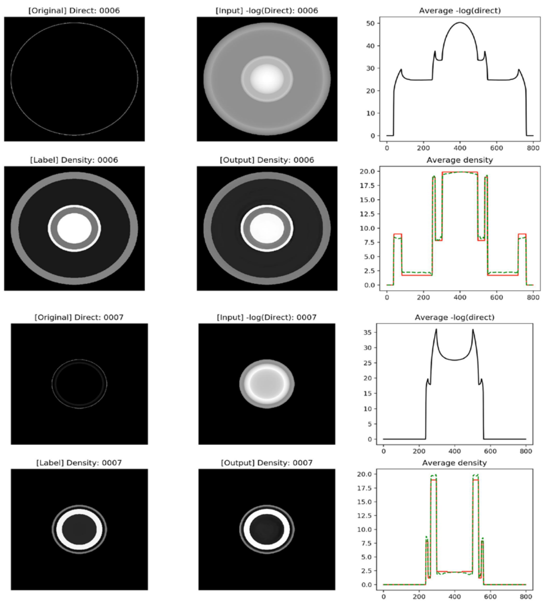
NRMSE Histogram for Test dataset

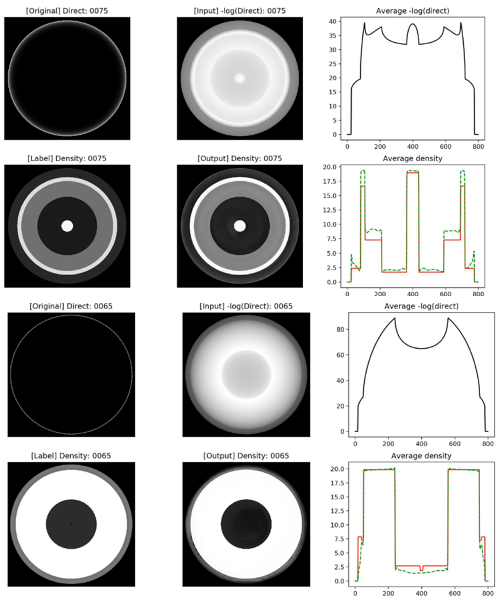


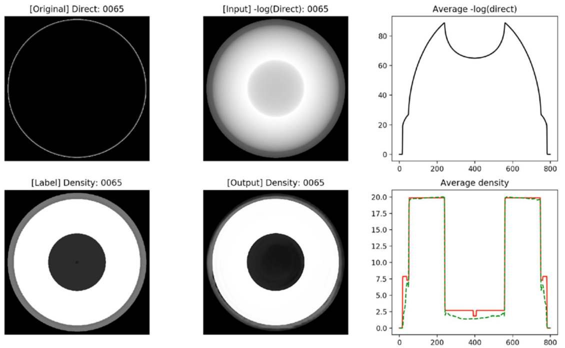
Red Case Excellent Performances Sample

Sample Very Good Performances

Good Performance

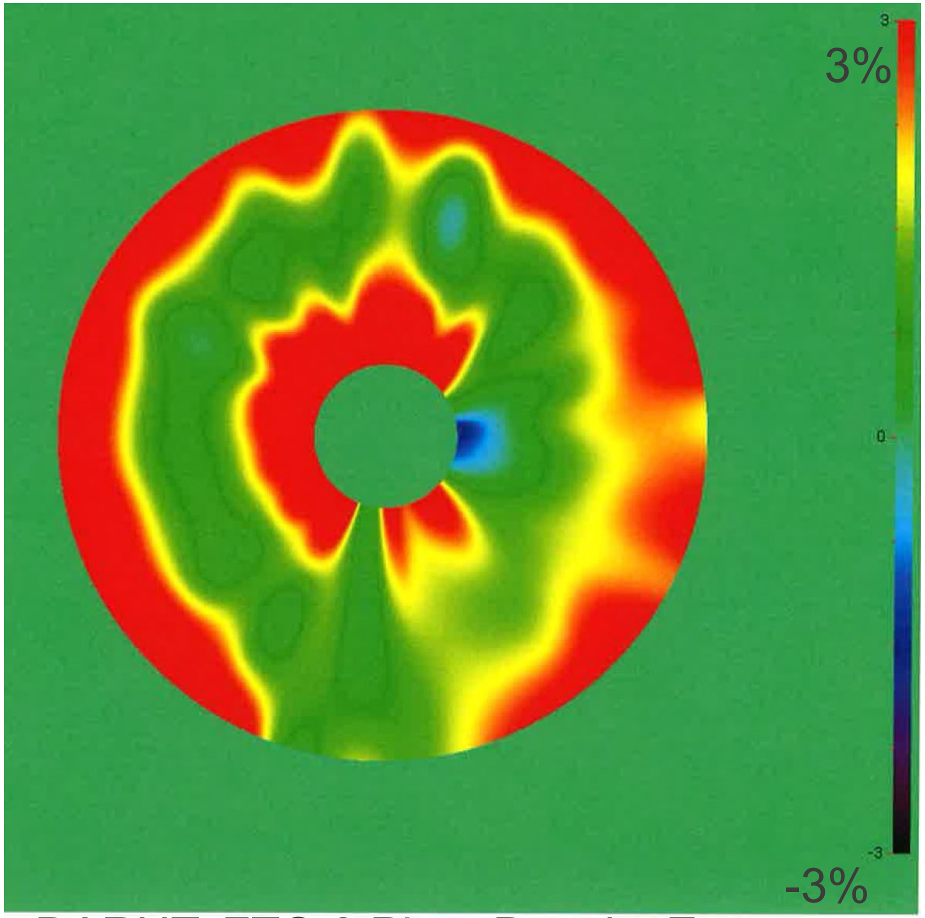






New physics based scatter local convolutional model significantly outperforms empirical BIE model

Percent Density Error



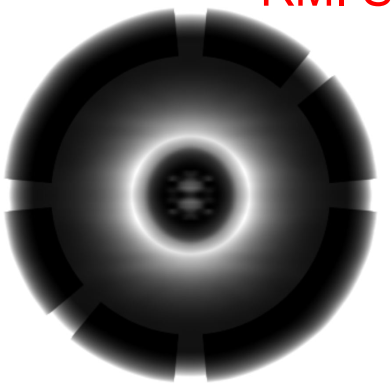
DARHT: FTO 0 Plate Density Errors
Empirical Model BIE

Percent Density Error

DARHT: FTO 0 Plate Density Errors
Physics Based De-Scattering Kernel Method

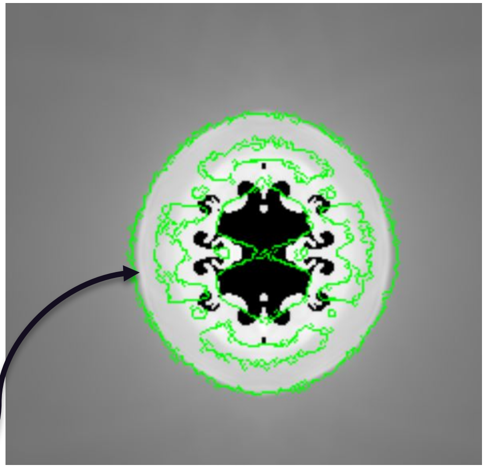
Can we extract shock and edge locations from Hydrodynamic Calculation & Radiographic Image

RMI Simulation



Transmission with Noise &Blur
Graded Collimation

Edges from Synthetic Radiograph Green



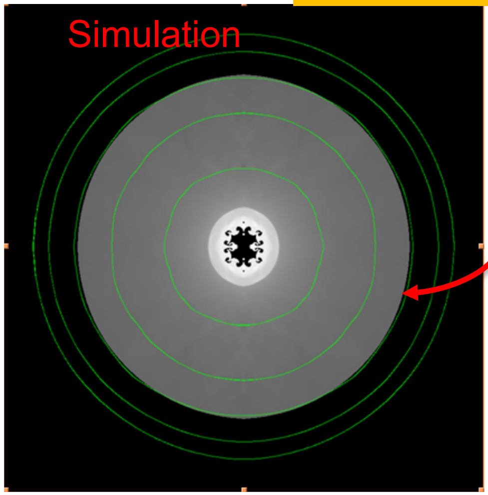
Blur+Noise Added

Large Blur+ Noise Added

Blur may cause some degradation In shock location

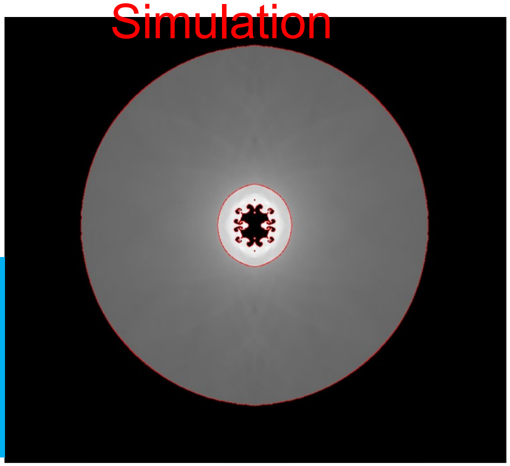
Solution uses reconstructed density fields to determine interfaces

Shock location may be determined reasonably well from transmission.



Edge location may be determined reasonably well from transmission i.e. must correct for parallax.

Feature Extraction Density Field from Hydrodynamic Calculation
Edge/Shot/Topology



Theoretical Hydrodynamics: Properties of Degenerate Solutions

Sedov Point Explosion Problem

Self-similar solution, normalized to a shock position:

- density profile: $\rho(r) = Ae^{-\omega r}$
- E: blast energy
- α: normalization

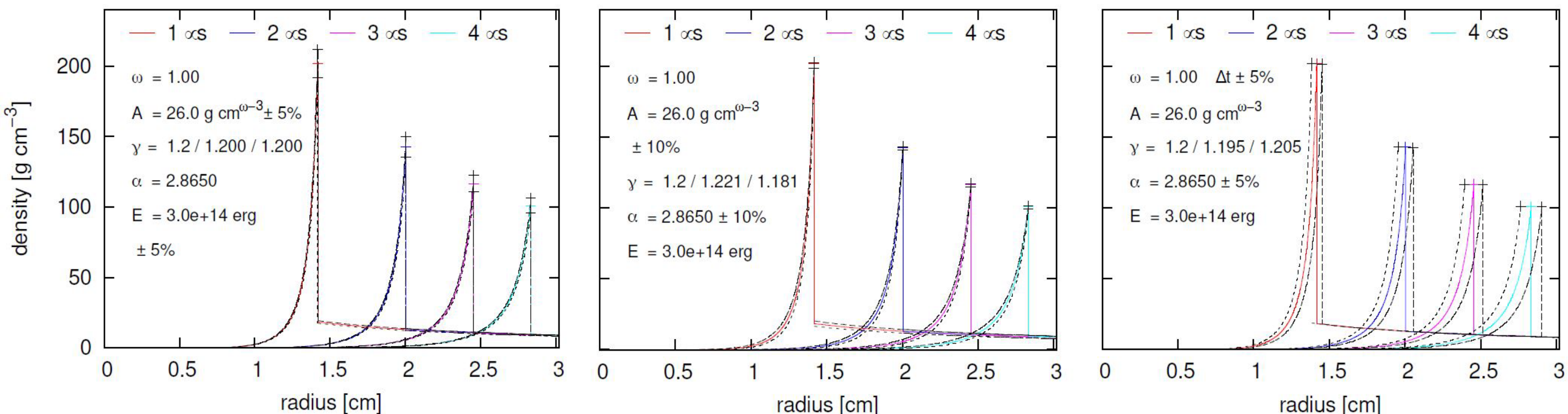
$$R_s(t) = \left(\frac{Et^2}{\alpha A}\right)^{\frac{1}{5-\omega}}$$

How much can density fields vary for invariant shock evolution?

Variation in density for fixed shock locations is totally dependent on range of parameters examined.

If group $\frac{Et^2}{\alpha A}$ is invariant for fixed ω shock evolution will remain invariant

Type 1: E/A = const. Type 2: αA = const. Type 3: t^2/α = const.



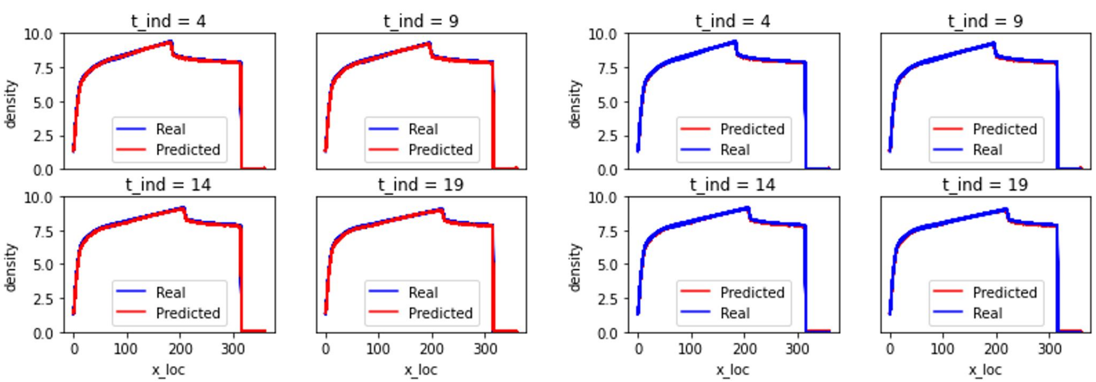
All other degeneracies are linear combination of these.

Demonstration of CGAN to Predict Density based on Shock and Edge Features

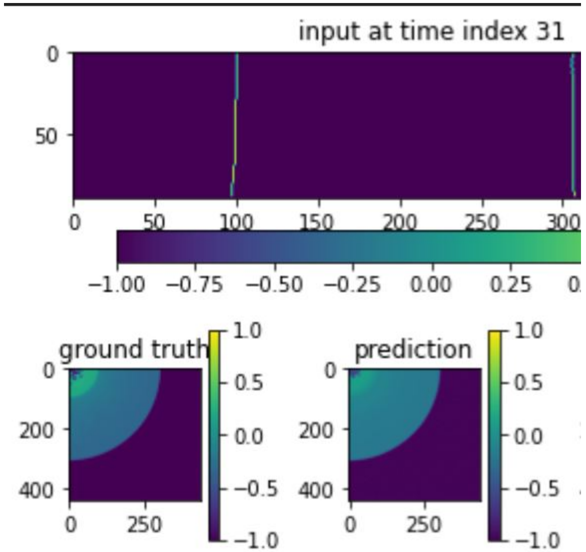
CGAN Architecture developed based on Pix2Pix, Phillip Isola Image-to-Image Translation with Conditional Adversarial Networks

Demonstration of density Inversion using a single temporal snap shot

CGAN Predictions



Density reconstructions using time-series of shock/edge to determine density 1 D Simulations



2 D RMI Simulations

Coupled Hydrodynamic & Radiographic Reconstructions

Objective: Learning the dynamic evolution of densities and learning a network between (clean) direct signals or radiographs and corresponding densities.

- The training data can be denoted as: $[D_i(t_1),\ \rho_i(t_1),\ D_i(t_2),\ \rho_i(t_2),\ D_i(t_3),\ \rho_i(t_3),\ D_i(t_{41}), \cdots, \rho_i(t_{41})]_{i=1}^{N}$, where D are the radiograph measurements, ρ is the clean densities, N denotes the number of time-series data sets and each time-series data point has 41 time snapshots.
- Learn a common model of the dynamics using CNNs as follows:

$$\rho_i(t_{j+1}) = G(\rho_i(t_j)), \quad j = 1, 2, \cdots, 41$$

where G is a deep CNN whose parameters we can learn from the above data set.

Coupled Hydrodynamic & Radiographic Reconstructions

- CNN for reconstructing density from radiograph measurement:

$$\rho_i(t_j) = F(D_i(t_j)), \quad j = 1, 2, \cdots, 41$$

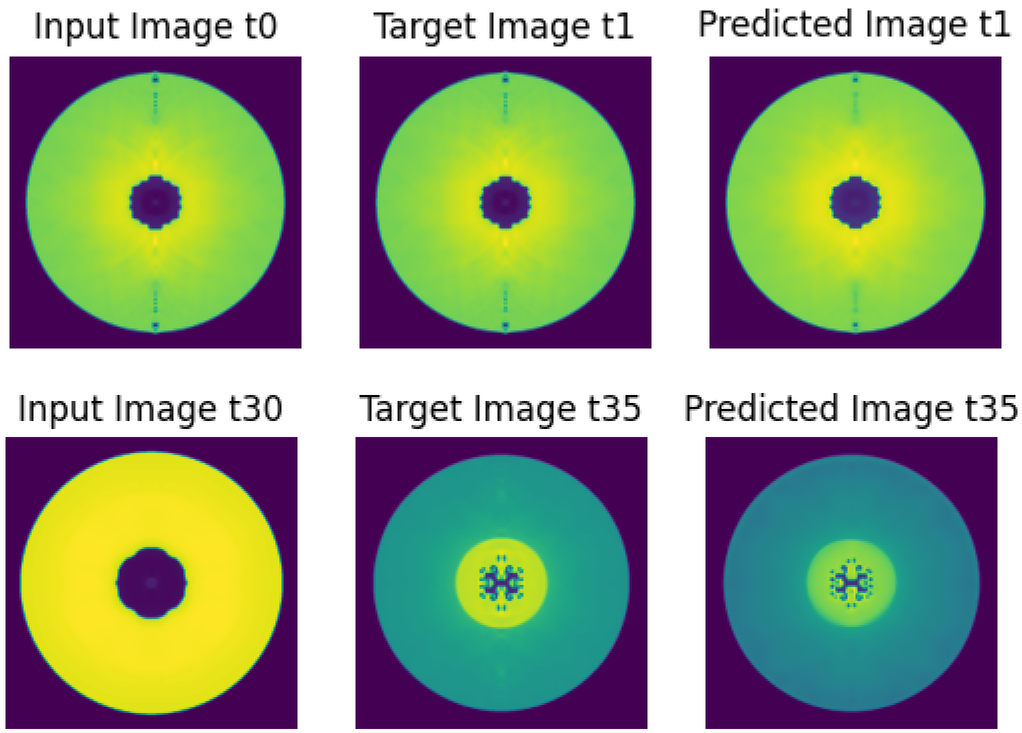
where $F(.)$ maps from clean direct signals to clean densities.

- For reconstruction time, we get $T(t_j)$ from which we can obtain an estimate $\hat{D}(t_j)$ and then obtain the densities by optimizing:

$$\min_{D(t_j), \rho(t_j) \geq 0} \sum_j (\mu ||\rho(t_j) - F(D(t_j))||^2 + \lambda ||\rho(t_j) - G(\rho(t_{j-1}))||^2 + ||D(t_j) - \hat{D}(t_j)||^2)$$

where the PDE model is replaced with a CNN-based regularizer.

Preliminary Dynamic Results



Simulations

Proximal Gradient Method for Parameter Estimation

Let $g(\psi) = \|\rho - f(\psi)\|_2^2/2$, where ρ is the density distribution associated with hydro dynamic parameters ψ.

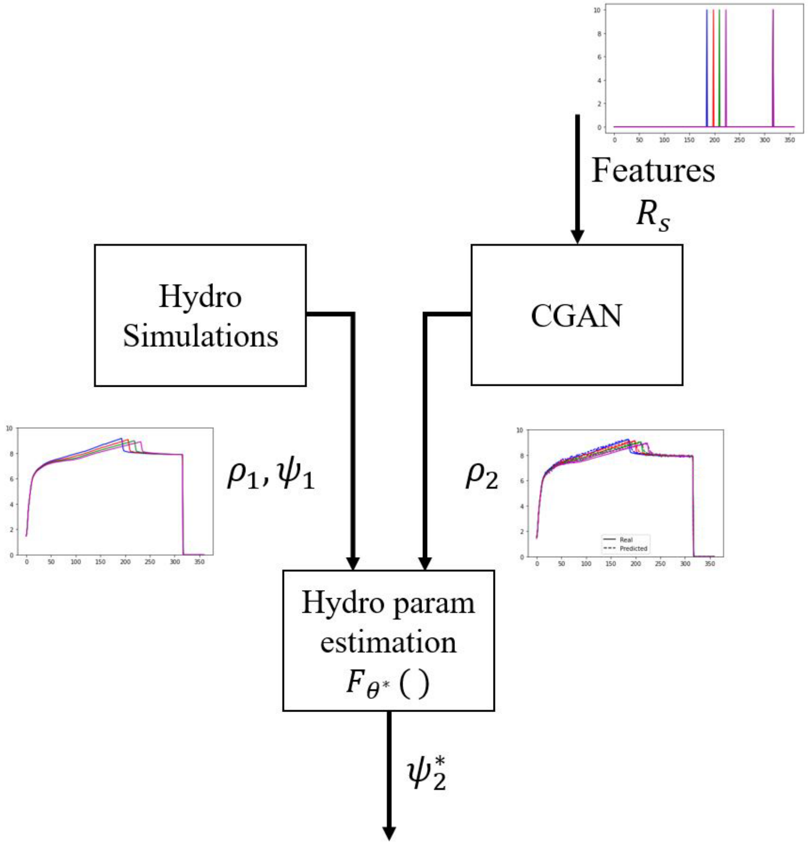
Let $\psi^* = \arg\min_{\psi} g(\psi)$

$$\psi^* = prox_{\lambda g}(\psi') \triangleq \arg\min_{\psi}\left\{g(\psi) + \frac{\|\psi - \psi\prime\|_2^2}{2\lambda}\right\}$$

$$\approx \psi' - \lambda \nabla_{\psi} f(\psi')$$

$$\frac{\partial f(\psi)}{\partial[\psi]_i} \approx \frac{\Delta f}{\Delta[\psi]_i}, \Delta f = \rho_{\psi_2} - \rho_{\psi_1}, \Delta\psi = \psi_2 - \psi_1$$

$$\theta^* = \arg\min_{\theta} \delta\left(F_\theta\left(\rho_{\psi_1}, \rho_{\psi_2}, \psi_1\right), \psi_2 - \psi_1\right)$$
$$\psi_2^* = \psi_1 + F_{\theta^*}\left(\rho_{\psi_1}, \rho_{\psi_2}, \psi_1\right)$$

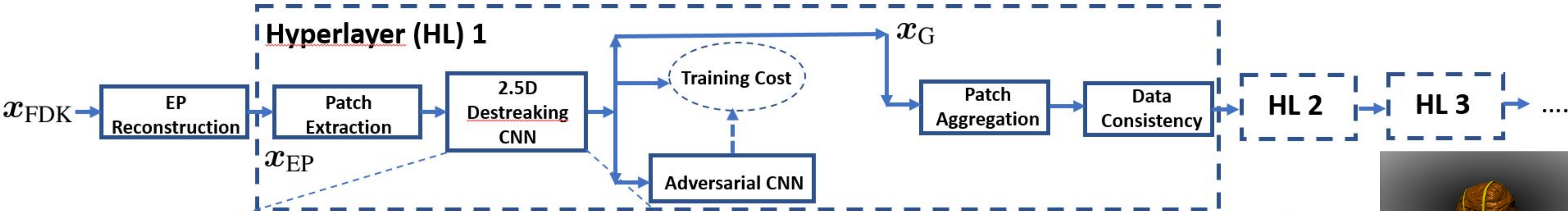


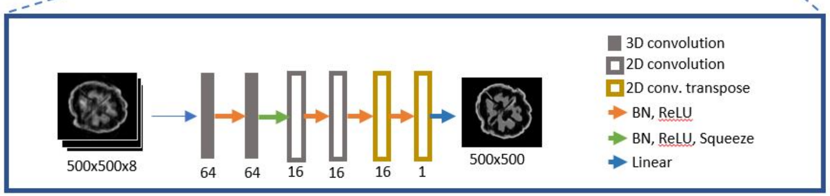
Reference: https://web.stanford.edu/~boyd/papers/pdf/prox_algs.pdf

1

Limited View Tomographic Reconstructions for DARHT Radiography

8 View Reconstruction

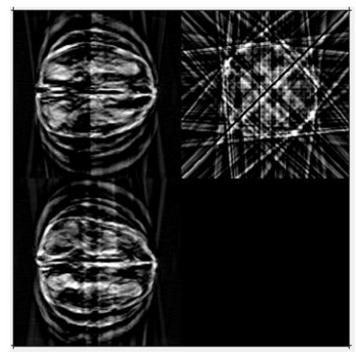


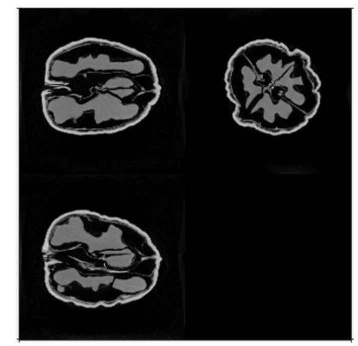


Extreme Limited View Micro-CT Reconstructions

GT

FDK





Training Cost

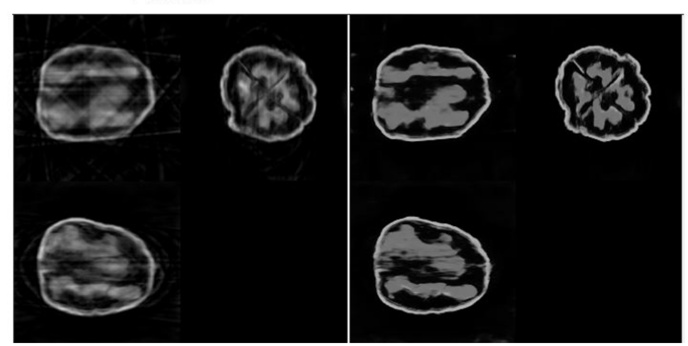
$$\min_{\theta_G} \; -\lambda \mathbb{E}\left[D(G(\mathcal{P}\boldsymbol{x}_{\mathrm{EP}};\theta_G))\right] + \mathbb{E}\left[\|\mathcal{P}\boldsymbol{x}_{\mathrm{GT}} - G(\mathcal{P}\boldsymbol{x}_{\mathrm{EP}})\|_1\right]$$

Data Consistency

$$\min_{\boldsymbol{x}} \; \|\boldsymbol{A}\boldsymbol{x} - \boldsymbol{y}\|_2^2 + \beta\|\boldsymbol{x} - \boldsymbol{x}_{\mathrm{G}}\|$$

PWLS-EP

PWLS-EP + GAN



Extensions to Hydrodynamics

Can we learn from a single 3D Simulation and reconstruct a 3D DARHT Image ?

2D Slice of 3D RMI Simulations

Walnut Reconstructions